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# Optimal Design of Power System Controller Using Breeder Genetic Algorithm

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## 1. Introduction

Genetic Algorithms (GAs) have recently found extensive applications in solving global optimization problems (Mitchell, 1996). GAs are search algorithms that use models based on natural biological evolution (Goldberg, 1989). They are intrinsically robust search and optimization mechanisms and offer several advantages over traditional optimization techniques, including the ability to effectively search large space without being caught in local optimum. GAs do not require the objective function to have properties such as continuity or smoothness and make no use of Hessians or gradient estimates.

In the last few years, Genetic Algorithms (GAs) have shown their potentials in many fields, including in the field of electrical power systems. Although GAs provide robust and powerful adaptive search mechanism, they have several drawbacks (Mitchell, 1996). Some of these drawbacks include the problem of “genetic drift” which prevents GAs from maintaining diversity in its population. Once the population has converged, the crossover operator becomes ineffective in exploring new portions of the search space. Another drawback is the difficulty to optimize the GAs’ operators (such as population size, crossover and mutation rates) one at a time. These operators (or parameters) interact with one another in a nonlinear manner. In particular, optimal population size, crossover rate, and mutation rate are likely to change over the course of a single run (Baluja, 1994). From the user’s point of view, the selection of GAs’ parameters is not a trivial task. Since the ‘classical’ GA was first proposed by Holland in 1975 as an efficient, easy to use tool which can be applicable to a wide range of problems (Holland, 1975), many variant forms of GAs have been suggested often tailored to specific problems (Michalewicz, 1996). However, it is not always easy for the user to select the appropriate GAs parameters for a particular problem at hand because of the huge number of choices available. At present, there is a little theoretical guidance on how to select the suitable GAs parameters for a particular problem (Michalewicz, 1996). Still another problem is that the natural selection strategy used by GAs is not immune from failure. To cope with the above limitations, an extremely versatile and effective function optimizer called Breeder Genetic Algorithm (BGA) was recently proposed (Muhlenbein, 1994). BGA is inspired by the science of breeding animals. The main idea is to use a selection strategy based on the concept of animal breeding instead of “natural selection” (Irhamah & Ismail, 2009). The assumption behind this strategy is as follows: “mating two individuals with high fitness is more likely to produce an offspring of high fitness than mating two randomly selected individuals”.

Some of the features of BGA are:

- BGA uses real-valued representation as opposed to binary representation used in classical GAs.
- BGA only requires a few parameters to be chosen by the user.
- The selection technique used is (always) truncation, whereby a selected top  $T\%$  of the fittest individuals are chosen from the current generation and goes through recombination and mutation to form the next generation. The rest of the individuals are discarded.

The main advantage of using BGA is its simplicity with regard to the selection method (Irhamah & Ismail, 2009) and the fewer parameters to be chosen by the user. However, there is a price to pay for this simplicity. Since only the best individuals are selected in each generation to produce the children for the next generation, there is a likelihood of premature convergence. As a result, BGA may converge to local optimum rather than the desired global one. It should be mentioned that most of the Evolutionary Algorithms including GA have problems with premature convergence to a certain degree. The general way to deal with this problem is to apply mutation to a few randomly selected individuals in the population. In this work, instead of a fixed mutation rate, we have used adaptive mutation strategy (Green, 2005), (Sheetekela & Folly, 2010). This means that the mutation rate is not fixed but varies according to the convergence and performance of the population. In general, even with fixed mutation rate, BGA may still perform better than GA as discussed in (Irhamah & Ismail, 2009).

The application of Evolutionary Algorithm to design power system stabilizer for damping low frequency oscillations in power systems has received increasing attention in recent years, see for example, (Wang, *et al* 2008), (Chuang, & Wu, 2006), (Chuang, & Wu, 2007), (Eslami, *et al* 2010), (Hongesombut, *et al* 2005), (Folly, 2006), and (Hemmati, *et al* 2010).

Low frequency oscillations in power systems arise due to several causes. One of these is the heavy transfer of power over long distance. In the last few years, the problems of low frequency oscillations are becoming more and more important. Some of the reasons for this are:

- a. Modern power systems are required to operate close to their stability margins. A small disturbance can easily reduce the damping of the system and drive the system to instability.
- b. The deregulation and open access of the power industry has led to more power transfer across different regions. This has the effect of reducing the stability margins.

For several years, traditional control methods such as phase compensation technique (Hemmati *et al*, 2010), root locus (Kundur, 1994), pole placement technique (Shahgholian & Faiz, 2010), etc. have been used to design Conventional PSSs (CPSSs). These (CPSSs) are widely accepted in the industry because of their simplicity. However, conventional controllers cannot provide adequate damping to the system over a wide range of operating conditions. To cover a wide range of operating conditions when designing the PSSs several authors have proposed to use multi-power conditions, whereby the PSS parameters are optimized over a set of specified operating conditions using various optimization techniques such as sensitivity technique (Tiako & Folly, 2009), (Yoshimura & Uchida, 2000),

Differential Evolutionary (Wang, *et al* 2008), hybrid Differential Evolutionary (Chuang, & Wu, 2006), (Chuang, & Wu, 2007), Particle Swarm Optimization (Eslami, *et al* 2010), Population-Based Incremental Learning (Folly, 2006), (Sheetekela, 2010), etc.

In this chapter, Breeder Genetic Algorithm (BGA) with adaptive mutation is used for the optimization of the parameters of the Power System Stabilizer (PSSs). An eigenvalue based objective function is employed in the design such that the algorithm maximizes the lowest damping ratio over specified operating conditions. A single machine infinite bus system is used to show the effectiveness of the proposed method. For comparison purposes, Genetic Algorithms (GAs) based PSS and the Conventional PSS (CPSS) are included. Frequency and time domain simulations show that BGA-PSS performs better than GA-PSS and CPSS under both small and large disturbances for all operating conditions considered in this work. GA-PSS in turn gives a better performance than the Conventional PSS (CPSS).

## 2. Background theory to breeder genetic algorithm

BGA is a relatively new evolution algorithm. It is similar to GAs with the exception that it uses artificial selection and has fewer parameters. Also, BGA uses real-valued representation as opposed to GAs which mainly uses binary and sometimes floating or integer representation. In this work, a modified version of BGA called Adaptive Mutation BGA is used (Green, 2005), (Sheetekela & Folly, 2010). Truncation selection method is adopted whereby a top  $T\%$  of the fittest individuals are chosen from the current population of  $N$  individuals and goes through recombination and mutation to form the next generation. The rest of the individuals are discarded. In truncation method, the fittest individual in the population called an *ellist* is guaranteed a place in the next generation. The other top  $(T-1)\%$  goes through recombination and mutation to form up the rest of the individuals in the next generation. The process is repeated until an optimal solution is obtained or the maximum number of iteration is reached.

### 2.1 Recombination

Recombination is similar to crossover in GAs (Michalewicz, 1996). The Breeder Genetic Algorithm proposed in this work allows various possible recombination methods to be used, each of them searching the space with a particular bias. Since there is no prior knowledge as to which bias is likely to suit the task at hand, it is better to include several recombination methods and allow selection to do the elimination. Two recombination methods were used in this work: volume and line recombination (Sheetekela, 2010).

In volume recombination, a random vector  $r$  of the same length as the parent is generated and the child  $z_i$  is produced by the following expression.

$$z_i = r_i x_i + (1 - r_i) y_i \quad (1)$$

where  $x_i$  and  $y_i$  are the two parents.

In other words, the child can be said to be located at a point inside the hyper box defined by the parents as shown in Fig. 1.

In line recombination, a single uniformly random number  $r$  is generated between 0 and 1, and the child is obtained by the following expression (Green, 2005).

$$z_i = rx_i + (1 - r)y_i \quad (2)$$

where  $x_i$  and  $y_i$  are the two parents.

In light of this, a child can be said to be located at a randomly chosen point on a line connecting the two parents as shown in Fig.2.

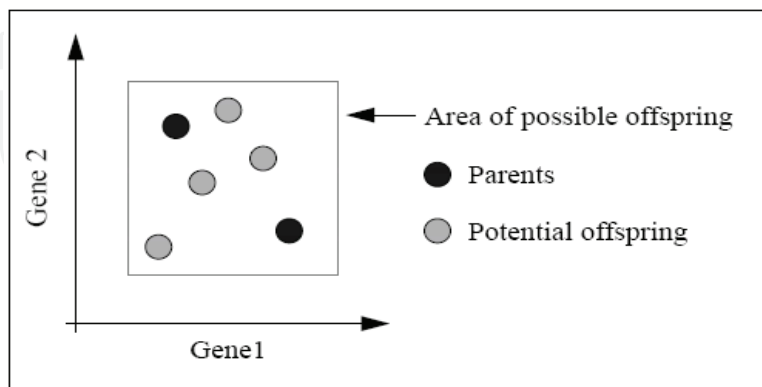


Fig. 1. Volume recombination

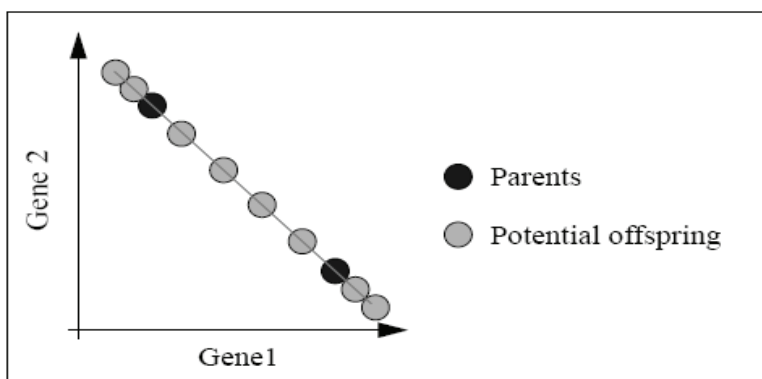


Fig. 2. Line recombination

## 2.2 Mutation

One problem that has been of concern in GAs is premature convergence, whereby a good but not optimal solution will come to dominate the population. In other words, the search may well converge to local optimum than the desired global one. This problem can be eliminated by adding a small vector of normally-distributed zero-mean random numbers (say with a standard deviation  $R$ ) to each child before inserting it into the population. The magnitude of the standard deviation  $R$  of the vector is very critical, as small  $R$  might lead to premature converge and large  $R$  might impair the search and reduce its ability to converge optimally. Therefore, it's better to use an adaptive approach whereby the rate of mutation is modified during the course of the search. We set  $R$  to the nominal rate  $R_{nom}$ . The population is divided into two halves  $X$  and  $Y$ . A mutation rate of  $2R_{nom}$  is applied to  $X$  whereas a mutation of  $R_{nom}/2$  is applied to  $Y$ . The mutation rate  $R_{nom}$  is adjusted depending on the population ( $X$  or  $Y$ ) that is producing better and fitter solutions on average. If  $X$  individuals are fitter, then the mutation rate  $R_{nom}$  is increased slightly by say 10%. If  $Y$  is fitter then the mutation rate,  $R_{nom}$  is reduced by a similar amount.

3. Test model

The power system considered is a single machine infinite bus (SMIB) system as shown in Fig. A. 1 of Appendix 8.2.1. The generator is connected to the infinite bus through a double-circuit transmission line. The generator is modeled using a 6<sup>th</sup> order machine model, and is equipped with an automatic voltage regulator (AVR) which is represented by a simple exciter of first order differential equation as given in the Appendix 8.1.4. The block diagram of the AVR is shown in Fig. A. 2 of Appendix 8.2.2. A supplementary controller also known as power system stabilizer (PSS) is to be designed to damp the system’s oscillations. The block diagram of the PSS is shown in Fig. A.3 of Appendix 8.2.3.

The non-linear differential equations of the system are linearized around the nominal operating condition to form a set of linear equations as follows:

$$\begin{cases} \frac{d}{dt}x = Ax + Bu \\ y = Cx + Du \end{cases} \tag{3}$$

where:

$A$  is the system state matrix,  $B$  is the system input matrix,  $C$  is the system output matrix and  $D$  is the feed-forward matrix

$x$  is the vector of the system states,  $u$  is the vector of the system inputs and  $y$  is the vector of the system outputs.

In this work,  $x = [\Delta\delta \ \Delta\omega \ \Delta\psi_{fd} \ \Delta\psi_{1d} \ \Delta\psi_{1q} \ \Delta\psi_{2q} \ \Delta E_{fd}]$ ;  $u = [\Delta T_m \ \Delta V_{ref}]$ ;  $y = \Delta\omega$ ; where,  $\Delta\delta$  is the rotor angle deviation,  $\Delta\omega$  is the speed deviation,  $\Delta\psi_{fd}$  is the field flux linkage deviation,  $\Delta\psi_{1d}$  is d-axis amortisseur flux linkage deviation,  $\Delta\psi_{1q}$  is the 1<sup>st</sup> q-axis amortisseur flux linkage deviation,  $\Delta\psi_{2q}$  is the 2<sup>nd</sup> q-axis amortisseur flux linkage deviation,  $\Delta E_{fd}$  is the exciter output voltage deviation.  $\Delta T_m$  is the mechanical torque deviation and  $\Delta V_{ref}$  is the voltage reference deviation.

Several operating conditions were considered for the design of the controllers. These operating conditions were obtained by varying the active power output,  $P_e$  and the reactive power  $Q_e$  of the generator as well as the line reactance,  $X_e$ . However, for simplicity, only three operating conditions will be presented in this paper. These operating conditions are listed in the Table 1 together with the open loop eigenvalues and their respective damping ratios in % in brackets.

case	Active Power Pe [p.u]	Reactive Power Qe [p.u]	Line reactance Xe [p.u]	Eigenvalues (Damping ratio)
1	1.1000	0.4070	0.7000	-0.2894 ± j5.2785 (0.0547)
2	0.5000	0.1839	1.1000	-0.3472 ± j4.3271 (0.0800)
3	0.9000	0.3372	0.9000	-0.2704 + j4.7212 (0.0572)

Table 1. Selected operating conditions with open-loop eigenvalues



#### 4. Fitness function

The fitness function is used to provide the measure of how individuals performed. In this instance, the problem domain was that the PSS parameters should stabilize the system simultaneously over a certain range of specified operating conditions. The PSS which parameters are to be optimized has a structure similar to the conventional PSS (CPSS) as shown in Fig. A. 3. of Appendix 8.2.3. There are three parameters  $K_s$ ,  $T_1$  and  $T_2$  that are to be optimized, where  $K_s$  is the PSS gain and  $T_1$  and  $T_2$  are lead-lag time constants.  $T_w$  is the washout time constant which is not critical and therefore has not been optimized.

The fitness function that was used is to maximize the lowest damping ratio. Mathematically the objective function is formulated as follows:

$$val = \max(\min(\zeta_{ij})) \quad (4)$$

where

$$i = 1, 2, \dots, n, j = 1, 2, \dots, m$$

$$\zeta_{ij} = \frac{-\sigma_{ij}}{\sqrt{\sigma_{ij}^2 + \omega_{ij}^2}}$$

$\zeta_{ij}$  is the damping ratio of the  $i^{\text{th}}$  eigenvalue of the  $j^{\text{th}}$  operating conditions. The number of the eigenvalues is  $n$ , and  $m$  is the number of operating conditions.

$\sigma_{ij}$  and  $\omega_{ij}$  are the real part and the imaginary part (frequency) of the eigenvalue, respectively.

#### 5. PSS design

The following parameter domain constraints were considered when designing the PSS.

$$0 < K_s \leq 20$$

$$0.001 \leq T_i \leq 5$$

where  $K_s$  and  $T_i$  denote the controller gain and the lead lag time constants, respectively .

##### 5.1 BGA-PSS

The following BGA parameters have been used during the design

- Population: 100
- Generation: 100
- Selection: Truncation selection (i.e., selected the best 15% of the population)
- Recombination: Line and volume
- Mutation initial  $R_{\text{nom}}$ : 0.01

The parameters of the BGA-PSS are given in Table A.1 of Appendix 8.2.3.

5.2 GA-P15 Folly\_secondSS

The following GA parameters have been used during the design

- Population: 100
- Generation: 100
- Selection: Normalized geometric
- Crossover: Arithmetic
- Mutation: Non-uniform

More information on the selection, crossover and mutation can be found in (Michalewicz, 1996), (Sheetekela & Folly, 2010).

The parameters of the GA-PSS are given in Table A.1 of Appendix 8.2.3.

5.3 Conventional-PSS

The Conventional PSS (CPSS) was designed at the nominal operating condition using the phase compensation method. The phase lag of the system was first obtained, which was found to be 20°, thus only a single lead-lag block was used for the PSS. After obtaining the phase lag, a PSS with a phase lead was designed using the phase compensation technique. The final phase lead obtained was approximately 18°, thus giving the system a slight phase lag of 2°. Once the phase lag is improved, then the damping needed to be improved as well by varying the gain  $K_s$ . The parameters of the CPSS are given in Table A.1 of Appendix 8.2.3.

6. Simulation results

6.1 Eigenvalue analysis

Under the assumption of small-signal disturbance (i.e, small change in  $V_{ref}$  or  $T_m$ ), the eigenvalues of the system are obtained and the stability of the system investigated. Table 2 shows the eigenvalues of the system for the different PSSs. The damping ratios are shown in brackets. For all of the cases, it can be seen that on average, BGA-PSS provides more damping to the system than GA-PSS. On the other hand, GA-PSS performs better than CPSS. For example for case 1, BGA-PSS provides a damping ratio of 50% as compared to 48.85% for GA-PSS and 44.93% for CPSS. This means that, BGA gives the best performance. Likewise, BGA provides better damping ratios for cases 2 and 3.

case	BGA-PSS	GA-PSS	CPSS
1	-3.0664 ±j 5.3117 (0.5000)	-2.9208 ± j5.2172 (0.4885)	-1.9876 ± j3.9516 (0.4493)
2	-1.2793 ± j4.3024 (0.2850)	-1.2305± j4.2616 (0.2774)	-0.9529 ± j3.9443 (0.2348)
3	-2.1245 + j4.6503 (0.4155)	-2.0268 + j4.5784 (0.4048)	-1.3865 + j3.8881 (0.3359)

Table 2. Closed-loop eigenvalues



It should be mentioned that a maximum damping ratio of 50% was imposed on the BGA and GA, otherwise, their damping ratios could have been higher. If the damping of the electromechanical mode is too high this could negatively affect other modes in the system.

6.2 Large disturbance

A large disturbance was considered by applying a three-phase fault to the system at 0.1 seconds. The fault was applied at the sending-end of the system (near bus 1 on line 2) for 200ms. The fault was cleared by disconnecting line 2. Fig. 3 to Fig. 5 show the speed responses of the system.

Figure 3 shows the speed responses of the generator for case 1. When the system is equipped with GA-PSS and BGA-PSS it settles around 3 seconds. On the other hand, the settling time of the system equipped with the CPSS is more than doubled (6 seconds). In addition, the subsequent oscillations are larger than those of BGA and GA PSSs.

Figure 4 shows the speed responses for case 2. The system equipped with CPSS is seen to have bigger oscillations as compared to the system equipped with BGA-PSS and GA-PSS. With both BGA and GA PSSs, the system settled in approximately 3.5 sec., whereas CPSS takes more than 6 sec. to settle down. The performances of the BGA-PSS and GA-PSS are quite similar, even though the BGA-PSS performs slightly better than the GA- PSS.

Figure 5 shows the speed responses of the system for case 3. It can be seen that the system equipped with BGA and GA PSS settled in less than 4 sec compared to more than 6 sec. for the CPSS. With CPSS, the system has large overshoots and undershoots.

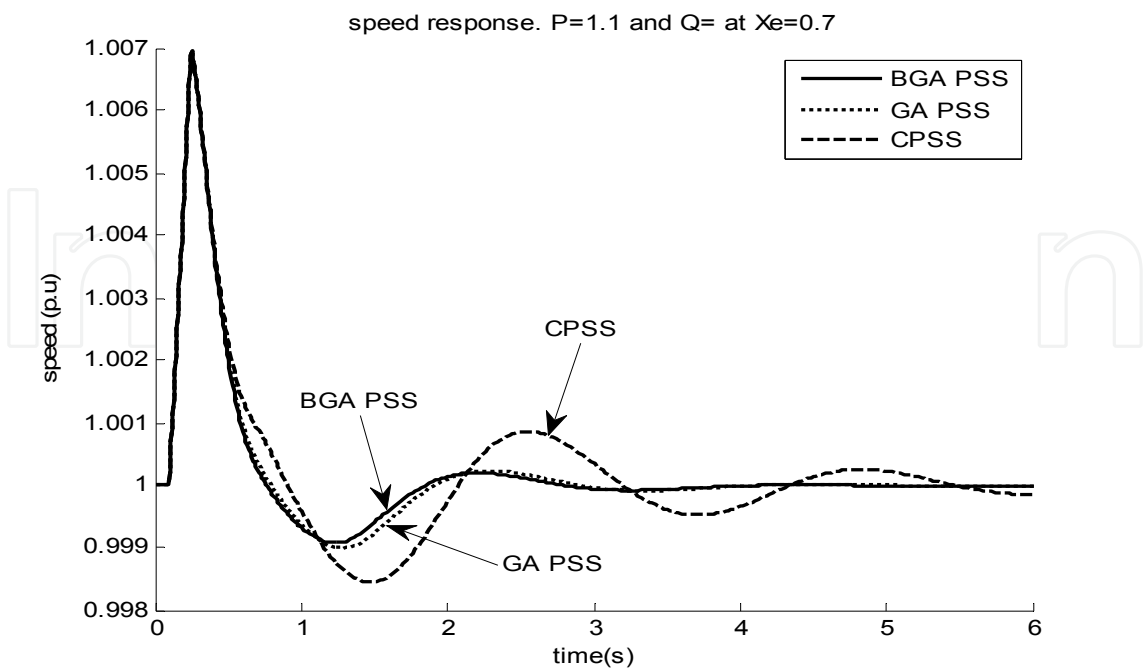


Fig. 3. Speed response of case 1 under three-phase fault

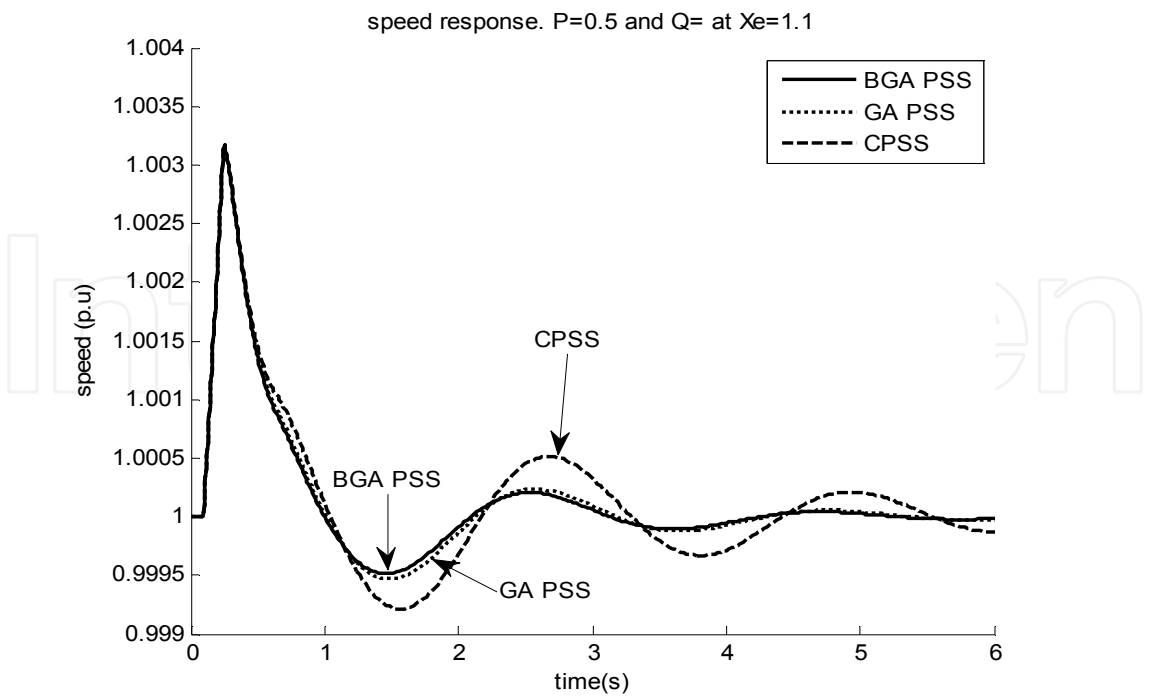


Fig. 4. Speed responses of case 2 under three-phase fault

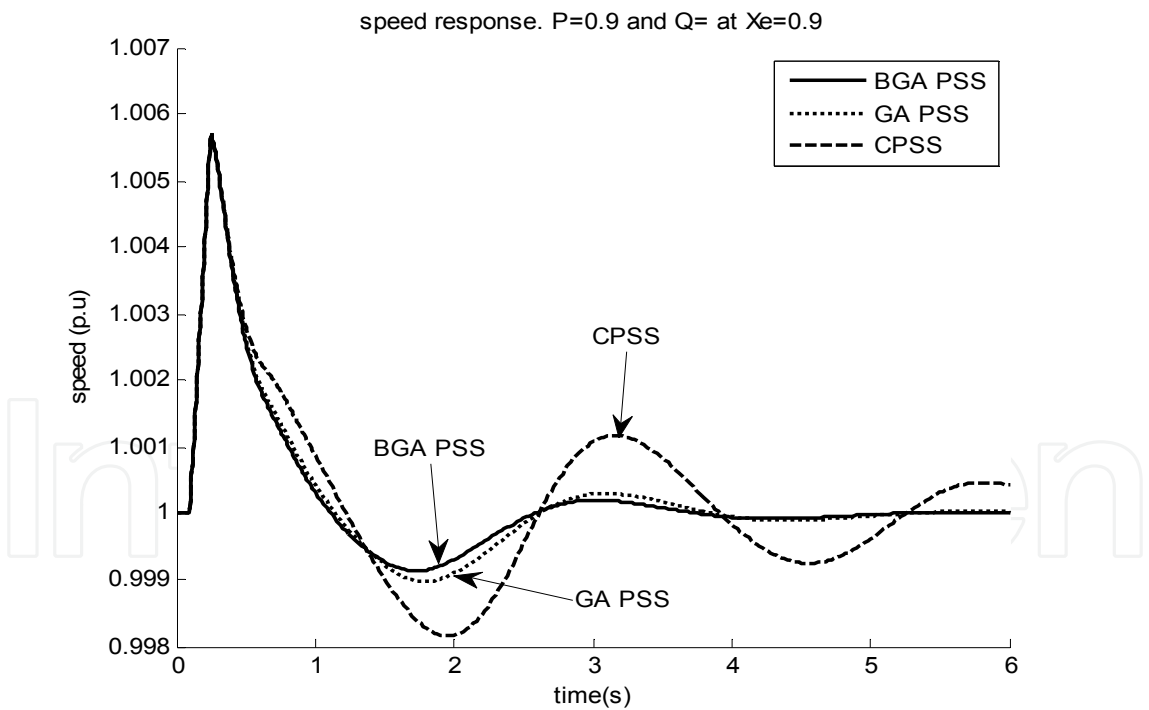


Fig. 5. Speed responses of case 3 under three-phase fault

7. Conclusion

Breeder Genetic Algorithms is an extremely versatile and effective function optimizer. The main advantage of BGA over GA is the simplicity of the selection method and the fewer

genetic parameters. In this work, adaptive mutation has been used to deal with the problem of premature convergence in BGA. The effectiveness of the proposed approach was demonstrated by the time and frequency domain simulation results. Eigenvalue analysis shows that the BGA based controller provides a better damping to the system for all operating conditions considered than a GA based controller. The conventional controller provides the least damping to all the operating conditions considered. The robustness of the BGA controller under large disturbance was also investigated by applying a three-phase fault to the system. Further research will be carried out in the direction of using multi-objective functions in the optimization and using a more complex power system model.

## 8. Appendix

### 8.1 Generator and Automatic Voltage Regulator (AVR) equations

#### 8.1.1 Swing equations

$$\frac{d}{dt}\Delta\omega = \frac{1}{2H}(T_m - T_e - K_D\Delta\omega)$$

$$\frac{d}{dt}\Delta\delta = \omega_0\Delta\omega$$

where

$\delta$  is the rotor angle in rad

$\omega$  is the synchronous speed in per-unit (p.u.)

$\omega_0$  is the synchronous speed in rad/sec

$H$  is the inertia constant in sec.

$T_m$  is the mechanical torque in p.u.

$T_e$  is the mechanical torque in p.u.

$K_D$  is the damping coefficient in torque/ p.u.

#### 8.1.2 Rotor circuit equations

$$\frac{d}{dt}\psi_{fd} = \omega_0(E_{fd} - \frac{R_{fd}}{L_{fd}}i_{fd})$$

$$\frac{d}{dt}\psi_{1d} = -\omega_0 R_{1d} i_{1d}$$

$$\frac{d}{dt}\psi_{1q} = -\omega_0 R_{1q} i_{1q}$$

$$\frac{d}{dt}\psi_{2q} = -\omega_0 R_{2q} i_{2q}$$

where

$\psi_{fd}$ ,  $\psi_{1d}$ ,  $\psi_{1q}$ ,  $\psi_{2q}$ ,  $E_{fd}$  are the same as defined in section 3.

$R_{fd}$ ,  $L_{fd}$  are the field winding resistance and inductance, respectively.

$R_{1d}$  is the d-axis amortisseur resistance.

$R_{1q}$  is the 1<sup>st</sup> q-axis amortisseur resistance.

$R_{2q}$  is the 2<sup>nd</sup> q-axis amortisseur resistance.

The rotor currents are expressed as follows:

$$i_{fd} = \frac{1}{L_{fd}}(\psi_{fd} - \psi_{ad})$$

$$i_{1d} = \frac{1}{L_{1d}}(\psi_{1d} - \psi_{ad})$$

$$i_{1q} = \frac{1}{L_{1q}}(\psi_{1q} - \psi_{aq})$$

$$i_{2q} = \frac{1}{L_{2q}}(\psi_{2q} - \psi_{aq})$$

where

$\psi_{fd}$ ,  $\psi_{1d}$ ,  $\psi_{1q}$ ,  $\psi_{2q}$  are defined as before

$\psi_{ad}$ ,  $\psi_{aq}$  are the mutual flux linkages in the d and q axis, respectively.

$L_{1d}$  is the d-axis amortisseur inductance.

$L_{1q}$  is the 1<sup>st</sup> q-axis amortisseur inductance.

$L_{2q}$  is the 2<sup>nd</sup> q-axis amortisseur inductance.

### 8.1.3 Electrical torque

The electrical torque is expressed by the following:

$$T_e = \psi_d i_q - \psi_q i_d$$

where  $\psi_d$  and  $\psi_q$  are the d and q axis flux linkages, respectively.

### 8.1.4 AVR equations

$$\frac{d}{dt} E_{fd} = \frac{K_A}{T_A} (V_{ref} - V_t) - \frac{E_{fd}}{T_A}$$

where  $K_A$  and  $T_A$  are the gain and time constant of the AVR.  $V_t$  is the terminal voltage of the generator.

In this work  $K_A=200$  and  $T_A = 0.05$  sec.

8.2 Power system model, AVR parameters and PSS block diagram and parameters

8.2.1 Power system model diagram

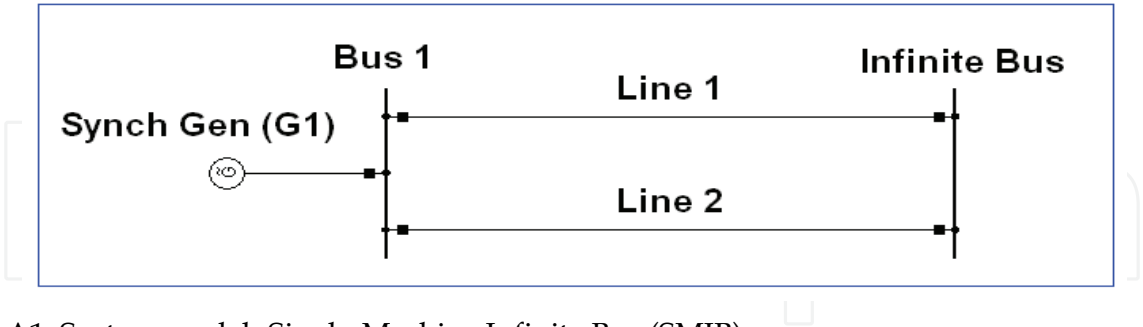


Fig. A1. System model- Single-Machine Infinite Bus (SMIB)

8.2.2 Block diagram of the Automatic Voltage Regulator (AVR)

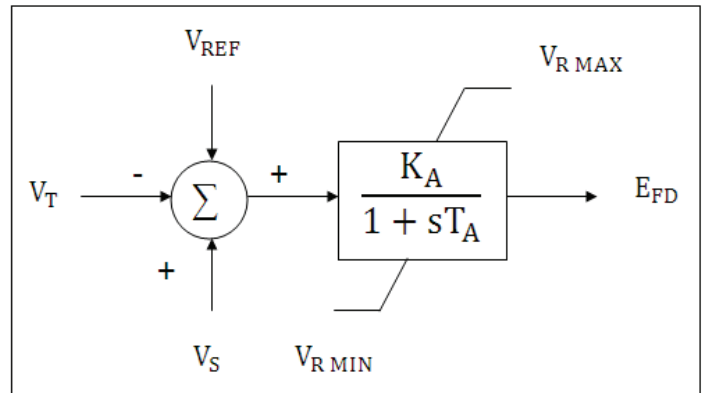


Fig. A2. Automatic voltage regulatore structure

8.2.3 Block diagram and parameters of the PSSs

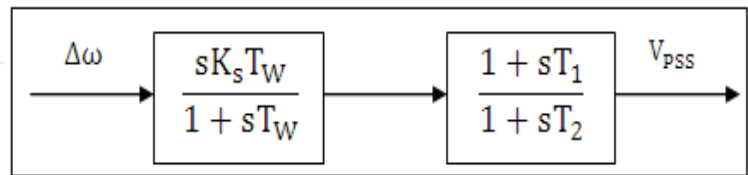


Fig. A3. Power system stabilizer structure

In Fig. A3,  $V_{PSS}$  is the output signal of the PSS, while  $\Delta\omega(s)$  is the input signal, which in this case is the speed deviation.

PSSs	$K_s$	$T_1$	$T_2$	$T_w$
CPSS	9.7928	1.1686	0.2846	2.5000
GA-PSS	13.7358	3.5811	1.2654	2.5000
BGA-PSS	18.8838	3.7604	1.7390	2.5000

Table A1. PSS parameters.

### 8.3 Generator's parameters

$X_l = 0.0742$  p.u.,  $X_d = 1.72$  p.u.,  $X'_d = 0.45$  p.u.,  $X''_d = 0.33$  p.u.,  $T'_{d0} = 6.3$  sec.,  $T''_{d0} = 0.033$  p.u.,  
 $X_q = 1.68$  p.u.,  $X'_q = 0.59$  p.u.,  $X''_q = 0.33$  p.u.,  $T'_{q0} = 0.43$  sec

$T''_{q0} = 0.033$  sec.,  $H = 4.0$  sec

### 8.4 Pseudo code for BGA generator's parameters

**Begin**

**Randomly initialize** a population of N individuals;

**Initialize** mutation rate  $R_{nom}$

**While** termination criterion not met

**evaluate** goodness of each individuals

**save** the best individual in the new population

**select** the best T% individuals and discarding the rest;

**for** I =1 to N-1 **do**

**randomly** select two individuals among the T% best individual

**recombine** the two parents to obtain one offspring

**end**

**divide** the new population into two halves (X and Y)

**apply** mutation rate  $r_{nom}/2$  to X and  $2 R_{nom}$  to Y

**evaluate** the average fitness value for the two half population (X and Y)

        If X performs better than Y; assign  $r = R_{nom} - 0.1 r_{nom}$ ;

        If Y performs better than X; assign  $r = R_{nom} + 0.1 r_{nom}$ ;

**end**

**end**

## 9. Acknowledgment

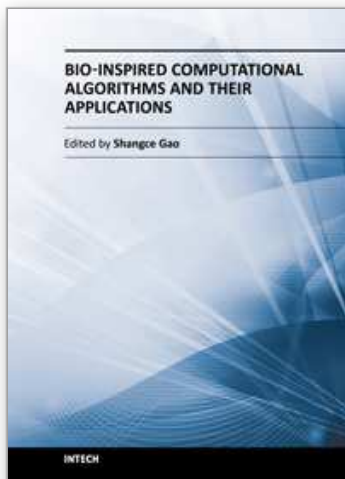
The authors would like to acknowledge the financial support of THRIP and TESP.

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## **Bio-Inspired Computational Algorithms and Their Applications**

Edited by Dr. Shangce Gao

ISBN 978-953-51-0214-4

Hard cover, 420 pages

**Publisher** InTech

**Published online** 07, March, 2012

**Published in print edition** March, 2012

Bio-inspired computational algorithms are always hot research topics in artificial intelligence communities. Biology is a bewildering source of inspiration for the design of intelligent artifacts that are capable of efficient and autonomous operation in unknown and changing environments. It is difficult to resist the fascination of creating artifacts that display elements of lifelike intelligence, thus needing techniques for control, optimization, prediction, security, design, and so on. Bio-Inspired Computational Algorithms and Their Applications is a compendium that addresses this need. It integrates contrasting techniques of genetic algorithms, artificial immune systems, particle swarm optimization, and hybrid models to solve many real-world problems. The works presented in this book give insights into the creation of innovative improvements over algorithm performance, potential applications on various practical tasks, and combination of different techniques. The book provides a reference to researchers, practitioners, and students in both artificial intelligence and engineering communities, forming a foundation for the development of the field.

### **How to reference**

In order to correctly reference this scholarly work, feel free to copy and paste the following:

K. A. Folly and S. P. Sheetekela (2012). Optimal Design of Power System Controller Using Breeder Genetic Algorithm, Bio-Inspired Computational Algorithms and Their Applications, Dr. Shangce Gao (Ed.), ISBN: 978-953-51-0214-4, InTech, Available from: <http://www.intechopen.com/books/bio-inspired-computational-algorithms-and-their-applications/optimal-design-of-power-system-controller-using-breeder-genetic-algorithm>

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